Biogeography Based Optimization Approach for Optimal Power Flow Problem Considering Valve Loading Effects

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***Abstract*— This paper presents a novel Biogeography Based Optimization (BBO) algorithm for solving multi-objective constrained optimal power flow problems in power system. In this paper, the feasibility of the proposed algorithm is demonstrated for IEEE 30-bus system with three different objective functions and it is compared to other well established population based optimization techniques. A comparison of simulation results reveals better solution quality and computation efficiency of the proposed algorithm over particle swarm optimization (PSO), Real Coded Genetic algorithm (RGA) for the global optimization of multi-objective constrained OPF problems.**

***Index Terms*— Biogeography, Optimal Power Flow, Particle Swarm Optimization, Genetic Algorithm, Evolutionary Programming, Mutation, Migration.**

I. INTRODUCTION

Optimal Power Flow (OPF) problem may be defined as determining the optimal settings of a given power system network that optimizes a certain objective function while satisfying power flow equations and inequality constraints like system security and equipments operating limits. Several conventional optimization techniques such as linear programming, interior point method, reduced gradient method and Newton method [1, 2], have been applied to solve OPF problem assuming continuous, differentiable and monotonically increasing cost function. However, higher order nonlinearities and discontinuities are observed in practical input-output characteristics due to valve point loading. Conventional methods have failed in handling nonconvex and nondifferentiable optimization problems. In the recent years, many evolutionary algorithms (EA) like GA [3-5] simulated annealing (SA) [6], particle swarm optimization (PSO) [7-10], EP [11], and hybrid evolutionary programming (HEP) [12], ant colony optimization (ACO) [13] and Bacteria foraging optimization (BFO) [14] have been proposed to solve non-convex, non-smooth and non-differentiable optimization problems.

Amongst the above population based algorithms, the annealing schedule of SA should be tuned carefully; otherwise it may produce suboptimal solutions. The GA method is usually faster than SA method because GA has parallel search technique. Traditional GA also differs from EP in two aspects; EP primarily relies on mutation and selection, but no crossover like traditional GA and EP uses the real values of control parameters but not their coding as in traditional GA. Hence, considerable computation time may be saved in EP. Real coded GA (RGA) [5] has been introduced to solve the OPF problems more efficiently with significant reduction in the computation time. ACO is based on foraging behavior of ant species. Solution candidates, called ants in ACO, communicate with other members of the ant colony by depositing pheromone to mark a path. High concentrations of pheromones indicate more favorable paths that other members should follow in order to reach the optimal solution. BFO is a bio-inspired technique, applied to solve power system optimization problems by Ghoshal et al. [14], but its optimization time is very high.

Biogeography based optimization (BBO) [15] is a new optimization algorithm and it has never been used in power system optimization so far. The application of biogeography to optimization has been first presented in [15] and it describes how a natural process can be modelled to solve general optimization problems.

This paper presents BBO algorithm for solving multi-objective OPF problem of IEEE 30-bus system. The simulation results of BBO algorithm are compared to the results of PSO, and RGA and the computation efficiency is found to be more efficient in BBO than other conventional methods.

II. MATHEMATICAL PROBLEM FORMULATION

A. Objective Function

In this paper, three different objective functions are considered to determine the effectiveness of the proposed algorithm. The objective functions are as follow:

1) Minimization of Fuel Cost

The aim of this objective function is to minimize the total fuel cost having valve point effect, while satisfying all equality and inequality constraints and it is formulated as:

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$$f_1(x,y)=\sum_{i=1}^{NG} a_i P_{gi}^{\ 2}+b_i P_{gi}+c_i+\left|d_i\times\sin\left(e_i\times\left(P_{gi}^{\min}-P_{gi}\right)\right)\right| \quad (1)$$

2) Minimization of Fuel Cost and voltage deviation

The objective of this type of problem is to minimize the voltage deviations of buses and fuel cost of the generating units and may be mathematically modelled as follows [2]:

$$f_2(x,y)=\sum_{i=1}^{NG} a_i P_{gi}^{\ 2}+b_i P_{gi}+c_i+\left|d_i\times\sin\left(e_i\times\left(P_{gi}^{\min}-P_{gi}\right)\right)\right|+\sum_{i=1}^{NB}\frac{f_1(x,y)\times P_{di}}{P_d}\times\left|V_i-V_{ref}\right| \quad (2)$$

3) Minimization of Fuel cost and Transmission Loss

To reduce the transmission losses in addition to fuel cost, mathematical formulation of this objective function is formulated by (3) [2]:

$$f_3(x,y)=\sum_{i=1}^{NG} a_i P_{gi}^{\ 2}+b_i P_{gi}+c_i+\left|d_i\times\sin\left(e_i\times\left(P_{gi}^{\min}-P_{gi}\right)\right)\right|+\frac{f_1(x,y)}{P_d}\times P_{loss} \quad (3)$$

Subject to the following equality and inequality constraints:

$$\begin{cases} P_{gi}-P_{Li}=\sum_{j=1}^{NB}|V_i||V_j|\left(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}\right) \\ Q_{gi}-Q_{Li}=\sum_{j=1}^{NB}|V_i||V_j|\left(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}\right) \end{cases} \quad (4)$$

$$\begin{cases} V_{gi}^{\min}\le V_i\le V_{gi}^{\max} & i=1,2,\cdots,NG \\ P_{gi}^{\min}\le P_i\le P_{gi}^{\max} & i=1,2,\cdots,NG \\ Q_{gi}^{\min}\le Q_i\le Q_{gi}^{\max} & i=1,2,\cdots,NG \\ V_{Li}^{\min}\le V_{Li}\le V_{Li}^{\max} & i=1,2,\cdots,NL \\ S_{Li}\le S_{Li}^{\max} & i=1,2,\cdots,NTL \\ T_i^{\min}\le T_i\le T_i^{\max} & i=1,2,\cdots,NT \\ Q_{Ci}^{\min}\le Q_{Ci}\le Q_{Ci}^{\max} & i=1,2,\cdots,NC \end{cases} \quad (5)$$

where a_i,b_i,c_i,d_i,e_i : Cost coefficients of ith unit,

$P_{gi},Q_{gi},P_{Li},Q_{Li}$: Active & reactive power generation and load of i-th unit,

$V_{gi}^{\min},V_{gi}^{\max};V_{Li}^{\min},V_{Li}^{\max};P_{gi}^{\min},P_{gi}^{\max};q_{gi}^{\min},q_{gi}^{\max};T_i^{\min},T_i^{\max};Q_{ci}^{\min},Q_{ci}^{\max}$:Minimum and maximum generator voltages, load voltage, active and reactive power generations, tap setting and VAR injection of i-th unit respectively,

$S_{Li},S_{Li}^{\max}$: Loading and maximum loading of i-th line,

P_{loss},P_d,P_{di} : Total loss, total load and load of i-th bus,

NB, NG, NL, NC, NTL, NT : Number of buses, generator buses, load buses, shunt compensators, transmission lines and tap setting transformers.

III. Algorithms

A. Particle swarm optimization

In a PSO system, multiple candidate solutions coexist and collaborate simultaneously. Here each candidate solution is associated with a velocity. Each candidate solution, called a *particle*, flies in the problem space (similar to the search process for food of a bird swarm) looking for the optimal position. A *particle* with time adjusts its position according to its own memory and *cognitive experience*, while adjusting to the *social experience* of neighbouring particles as well. If a particle discovers a promising new solution, all the other particles will move closer to it, exploring the region more thoroughly in the process requiring less computational book keeping and generally few lines of code. Based on PSO concept, mathematical equations for the searching process are:

Velocity updating equation:

$$v_i^{k+1}=w\times v_i^k+c1\times r1\times(pBest_i-x_i^k)+c2\times r2\times(gBest-x_i^k) \quad (6)$$

Position updating equation: $$x_i^{k+1}=x_i^k+v_i^{k+1} \quad (7)$$

where x_i^k : current position of the i-th particle at k-th iteration, x_i^{k+1} :modified position of the of i-th particle, v_i^k : current velocity of the i-th particle at k-th iteration, v_i^{k+1} : modified velocity of the of i-th particle, $c1,c2$: weighting factors, $r1,r2$: random numbers in the interval [0, 1],

$pBest_i$: position best of i-th particle, $gBest$: group best, w : inertia weight factor.

Main steps of PSO techniques are given below:

- Initialization of floating point particles of n_p population, each consisting of the variable parameters,
- Evaluation of objective function value for each particle,
- Search for individual minimum objective function value and corresponding individual best particle,
- Search for global minimum objective function value and its corresponding global best particle,
- Selection of elite particles like GA's selection or Taguchi selection, copying them over the unselected particles,

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- Velocity updating,
- Position updating,
- Individual best particle updating,
- Global best particle updating,
- Iteration updating and stopping criteria.

B. Real Coded Genetic algorithm (RGA)

Traditional binary coded GA suffers from few drawbacks when applied to multi-dimensional and high-precision numerical problems. The situation can be improved if GA is used with real number data. Different steps of RGA are

- Real coded initialization of each chromosome.
- Selection operation based on computation of fitnesses and merit ordering
- Crossover and Mutation operation
- Sorting of the fitness values in increasing order among parents and off-springs
- Selection of the better chromosomes as parents of the next generation
- Updating of genetic cycle and stopping criterion.

C. Biogeography Based Optimization (BBO)

1) Overview of BBO technique

BBO [15] has been developed based on the theory of Biogeography [16]. BBO concept is mainly based on Migration and Mutation. The concept and mathematical formulation of Migration and Mutation steps are given below:

Migration: BBO algorithm [15] is similar to other population based optimization techniques where population of candidate solutions can be represented as vectors of real numbers. Each real number in the vector is considered as one suitability index variable (SIV). Fitness (in BBO, a term called habitat suitability index (HSI)) of each candidate solution is evaluated using its SIVs. HSI represents the quality of each candidate solution. High HSI solution represents better quality solution and low HSI solution represents inferior solution in the optimization problem. The emigration and immigration rates of each solution are used to probabilistically share information between habitats. Immigration rate (λ_s) and emigration rate (μ_s) can be evaluated by (8) and (9) [15]:

$$\lambda_s = I \cdot \left(1 - \frac{S}{S_{\max}}\right) \quad (8)$$

$$\mu_s = \frac{E \cdot S}{S_{\max}} \quad (9)$$

where I : maximum immigration rate,

E : maximum emigration rate,

S : nunber of species,

$S_{\max}$: maximum number of species,

Using Habitat Modification Probability each solution is modified based on other solutions. Immigration rate, λ_s of each solution is used to probabilistically decide whether or not to modify each SIV in that solution. If a SIV in a given solution is selected for modification, emigration rates, μ_s of other solutions are used to probabilistically select which of the solutions should migrate a randomly selected SIV to that solution. The main difference between recombination approach of evolutionary strategies (ES) and migration process of BBO is that in ES, global recombination process is used to create a completely new solution, while in BBO, migration is used to bring changes within the existing solutions. In order to prevent the best solutions from being corrupted by the immigration process, few elite solutions are kept in BBO algorithm.

Mutation: Due to some natural calamities or other events HSI of a natural habitat can change suddenly and it may deviate from its equilibrium value. In BBO, this event is represented by the mutation of SIV. Species count probabilities are used to determine mutation rates. The species count probability can be calculated using (10) [15].

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} & S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1} & 1 \le S \le S_{\max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} & S = S_{\max} \end{cases} \quad (10)$$

Each population member has an associated probability, which indicates the likelihood that it exists as a solution for a given problem. If the probability of a given solution is very low then that solution is likely to mutate to some other solution. Similarly if the probability of some other solution is high then that solution has very little chance to mutate. Therefore, very high HSI solutions and very low HSI solutions are equally improbable for mutation i.e. they have less chances to produce more improved SIVs in the later stage. But medium HSI solutions have better chances to create much better solutions after mutation operation. Mutation rate of each set of solution can be calculated in terms of species count probability using the equation (11) [15]:

$$m(s) = m_{\max}\left(\frac{1 - P_S}{P_{\max}}\right) \quad (11)$$

where $m(s)$:the mutation rate for habitat having S species,

$m_{\max}$: Maximum mutation rate,

$P_{\max}$: Maximum probability.

This mutation scheme tends to increase diversity among the populations. Without this modification, the highly probable solutions will tend to be more dominant in the population. This mutation approach makes both low and high HSI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier values. Few elite solutions are kept in mutation process to save the features of a solution, so if a solution

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becomes inferior after mutation process then previous solution (solution of that set before mutation) can revert back to that place again if needed. So, mutation operation is a high-risk process. It is normally applied to both poor and good solutions. Since medium quality solutions are in improving stage so it is better not to apply mutation on medium quality solutions.

Here, mutation of a selected solution is performed simply by replacing it with randomly generated new solution set. Other than this any other mutation scheme that has been implemented for GA can also be implemented for BBO.

2) BBO algorithm applied to OPF

In BBO algorithm, applied to the OPF problem, each candidate solution (i.e. each habitat) is defined by a vector with m SIVs where each SIV represents the value of independent variables such as active powers of all generators except slack bus, generators' voltages, tap settings of regulating transformers and reactive power injections. If there are *m* independent variables, then the i-*th* individual habitat H^i can be defined as follows:

$$H^i = SIV^{iq} = [SIV^{i1}, SIV^{i2}, ..., SIV^{im}] \quad (12)$$

where $i = 1,2,...,n; q = 1,2,...m$

where SIV^{iq} is the *q-th independent variable* of the

The algorithm of this method is as enumerated below.

Step 1**:** Initialization of the BBO parameters.

Step 2**;** The initial positions of SIVs (i.e. independent variables such as active powers of all generators except slack bus, generators' voltages, tap settings of regulating transformers and reactive power injections) of each habitat should be randomly selected while satisfying different equality and inequality constraints of OPF problems. Several numbers of habitats depending upon the population size are being generated. Each habitat represents a potential solution. It is similar to a chromosome string in GA.

Step 3**:** Perform load flow using any classical technique and determine all dependent variables such as load voltages, active power of slack bus, generators' reactive powers etc. In this paper load flow is performed by Newton-Raphson method.

Step 4**:** Calculate each HSI^i i.e. value of objective function for each i-th habitat of the population set n for given emigration rate μ_s, immigration rate λ_s and species S .

Step 5**:** Based on the HSI values elite habitats are identified.

Step 6**:** Each non-elite habitat is modified by performing probabilistically immigration and emigration operation as described in section III. C.1.

Step 7**:** Species count probability of each habitat is updated using (10). Mutation operation is performed on the non-elite habitat and HSI value of each new habitat is computed.

Step 8**:** Feasibility of a problem solution is verified i.e. each SIV should satisfy equality and inequality constraints.

Step 9**:** Go to step 3 for the next iteration.

Step 10**:** Stop iteration.

IV. Input Parameters

After several runs, the following input control parameters are found to be best for optimal performance of the proposed algorithm. Habitat Modification Probability, P^{mod} =1; Mutation Probability = 0.005, maximum immigration rate, I =1, maximum emigration rate, E =1, step size for numerical integration, dt =1, maximum iteration cycles = 100, elitism parameter = 4, number of SIVs = number of generator units and number of Habitats = population size =50.

V. Simulation results and discussions

The applicability and validity of all the algorithms have been tested on IEEE 30-bus system for multi-objective OPF problems. This system contains 6 generating units connected in bus no. 1, 2, 5, 8, 11 & 13; 30 buses, 4 regulating transformers connected between the line numbers 6-9, 6-10, 4-12 & 27-28; 2 shunt compensators connected in bus no. 10 & 14; 41 transmission lines. The bus data, transmission line data and load data of this system are taken from [17]. Generating unit capacity and cost coefficients data given in Table I. The voltage magnitudes of all buses are considered within the range of $[0.95\ p.u, 1.05\ p.u.]$. Tap settings of regulating transformers are within the range of $[0.9\ p.u., 1.1\ p.u.]$. The VAR injection of the shunt capacitors are taken within the interval of [0 p.u., 0.3 p.u.]. The programming has been written in MATLAB language, using MATLAB 7.1 on core 2 duo processor, 2.0 GHz with 1GB RAM.

The simulation results and convergence characteristics with three different objective functions namely, minimization of fuel cost, minimization of voltage deviation together with fuel cost and minimization of cost as well as transmission loss are given in Table II, Table III, Table IV, Fig. 1, Fig. 2 and Fig. 3 respectively. The active power, reactive power, bus voltage, VAR injection, tap settings, transmission loss (TL), summation of voltage deviation $(SVD = \sum |V_i - 1|)$ are on p.u. basis, fuel costs (FT) are in $/hr and computational times per iteration (CT) are in seconds . The simulation results show that BBO outperforms PSO and RGA in terms of solution quality (objective function, OF) and computation efficiency without violating any operating constraints.

Table I
genarating unit capacity and cost coefficients data

Bus No.	P_{min} p.u.	P_{max} p.u.	Q_{min} p.u.	Q_{max} p.u.	a $/h	b $/MWh	c $/MW^{2}h	d $/h	e rad/MW
1	0	0.8	0	0.1	0.02	2	0	300	0.2
2	0	0.8	-0.4	0.5	0.0175	1.75	0	200	0.22
5	0	0.4	-0.4	0.4	0.0250	3	0	200	0.35
8	0	0.5	-0.1	0.4	0.0625	1	0	150	0.42
11	0	0.3	-0.06	0.24	0.025	3	0	200	0.35
13	0	0.55	-0.06	0.24	0.00834	3.25	0	100	0.3

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Table II
Simulation results of case 1 with different algorithms

Alg.	PSO	RGA	BBO	Alg.	PSO	RGA	BBO
PG_1	0.7819	0.7845	0.6283	QC_{10}	0.2964	0.2764	0.2894
PG_2	0.5707	0.5691	0.7153	QC_{24}	0.0839	0.1038	0.1012
PG_5	0.3569	0.3601	0.3592	TC_{6-9}	1.0316	1.0661	0.9600
PG_8	0.3782	0.3811	0.4500	TC_{6-10}	0.9329	0.9387	0.9652
PG_{11}	0.2689	0.2696	0.1795	TC_{4-12}	0.9275	0.9851	0.9235
PG_{13}	0.5277	0.5216	0.5408	TC_{27-28}	1.0373	1.0683	0.9501
V_1	1.0019	0.9923	1.0471	OF	1074.5	1066.1	1058.7
V_2	0.9849	0.9761	1.0365	FC	1074.5	1066.1	1058.7
V_5	0.9678	0.9671	1.0165	TL	0.0503	0.0520	0.0394
V_8	0.9932	0.9912	1.0285	SVD	0.8073	0.9010	1.7648
V_{11}	1.0414	1.0328	1.0931	CT	14.201	12.653	13.391
V_{13}	1.0789	1.0381	1.0974				

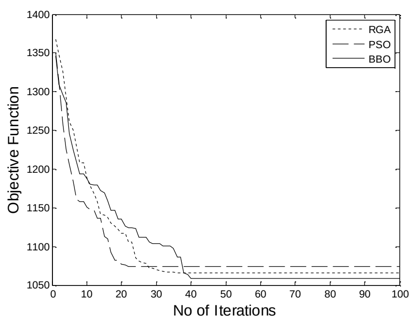

Fig. 1 Convergence Characteristics with different Algorithms (Case 1)

Table III
Simulation results of case 1 with different algorithms

Alg.	PSO	RGA	BBO	Alg.	PSO	RGA	BBO
PG_1	0.6247	0.6213	0.6253	QC_{10}	0.0911	0.0010	0.2921
PG_2	0.7111	0.7186	0.7211	QC_{24}	0.1915	0.1729	0.2863
PG_5	0.2741	0.2710	0.2695	TC_{6-9}	0.9588	1.0153	0.9974
PG_8	0.4619	0.4597	0.4687	TC_{6-10}	1.0329	0.9000	1.0274
PG_{11}	0.2690	0.2709	0.2683	TC_{4-12}	1.0065	1.0055	0.9873
PG_{13}	0.5402	0.5389	0.5295	TC_{27-28}	0.9473	0.9468	0.9668
V_1	1.0110	1.0150	1.0119	OF	1200.9	1197.4	1192.6
V_2	0.9989	1.0011	1.0013	FC	1191.3	1190.4	1184.1
V_5	0.9918	0.9941	0.9918	TL	0.0470	0.0464	0.0484
V_8	0.9999	1.0010	1.0013	SVD	0.3273	0.2582	0.2333
V_{11}	1.0401	1.0334	1.0123	CT	14.237	12.785	13.573
V_{13}	1.0155	1.0391	1.0142				

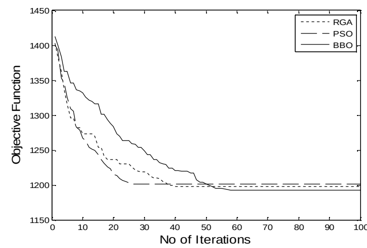

Fig. 2 Convergence Characteristics with different Algorithms (Case 2)

Table IV
Simulation results of case 3 with different algorithms

Alg.	PSO	RGA	BBO	Alg.	PSO	RGA	BBO
PG_1	0.6244	0.7703	0.6341	QC_{10}	0.2938	0.3000	0.3000
PG_2	0.7221	0.5779	0.7005	QC_{24}	0.1096	0.1045	0.0995
PG_5	0.3614	0.3604	0.3599	TC_{6-9}	0.9130	0.9782	1.1000
PG_8	0.3668	0.3711	0.3707	TC_{6-10}	1.0375	1.1000	0.9202
PG_{11}	0.2661	0.2695	0.2698	TC_{4-12}	0.9204	0.9681	0.9541
PG_{13}	0.5313	0.5231	0.5347	TC_{27-28}	0.9237	0.9749	0.9692
V_1	1.0559	.1000	1.1000	OF	1156.7	1152.5	1146.6
V_2	1.0480	1.0883	1.0905	FC	1141.3	1137.1	1132.3
V_5	1.0266	1.0836	1.0705	TL	0.0381	0.0383	0.0357
V_8	1.0409	1.0901	1.0851	SVD	2.1289	2.4912	2.5316
V_{11}	1.0986	1.1000	1.1000	CT	14.318	12.814	13.579
V_{13}	1.0911	1.1000	1.1000				

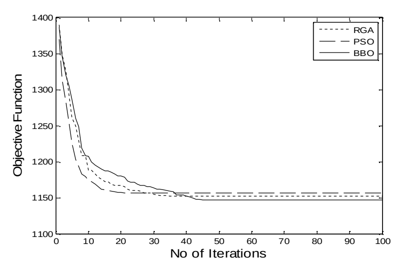

Fig. 3 Convergence Characteristics with different Algorithms (Case 3)

CONCLUSIONS

In this paper a novel Biogeography Based Optimization algorithm is proposed to solve multi-objective OPF problems. The test results clearly demonstrate that BBO outperforms other reported methods in terms of solution quality, computational efficiency, convergence characteristics for both IEEE 30-bus system. It is revealed that among all the algorithms, Biogeography Based Optimization is capable of achieving global optimal solution.

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